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Complex Architecture/ Indoor Navigation using Augmented Reality

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***Abstract*— Indoor navigation faces significant challenges, as traditional methods like GPS are ineffective in indoor environment. An Augmented Reality (AR)-based navigation system provides a promising solution by blending real-time interactive elements with indoor positioning technology. This paper surveys a cost-effective AR-based indoor navigation framework that integrates Simultaneous Localization and Mapping (SLAM), QR code repositioning, and the A* pathfinding algorithm. The system leverages mobile device sensors like accelerometers, gyroscopes, and cameras. To enhance spatial awareness and provide dynamic real-time navigation assistance, QR codes serve as exact reference points to fix SLAM drift errors, ensuring accurate user localization. AR-based visual guidance, with floating arrows and directional markers, makes the user experience better. The system operates independently of external technologies like GPS or Wi-Fi, enabling scalable deployment in complex indoor environments like train stations, shopping centers, and hospitals. Future upgrades will focus on AI-driven pedestrian flow analysis, better SLAM accuracy, and cloud-based data synchronization. Overall, this study demonstrates the potential of AR to transform indoor navigation by serving an interactive, accurate, and cost-effective solution to modern wayfinding challenges. Keywords—Indoor Navigation, Indoor Positioning, Augmented Reality, Simultaneous Localization and Mapping (SLAM), QR code, A* Pathfinding Algorithm, ARCore, NavMesh*.**

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I. INTRODUCTION

Indoor navigation poses significant challenges despite advancements in navigation technologies. Approaches such as digital maps are inadequate in indoor environments due to unreliable GPS signals and complex building architecture. Existing indoor positioning technologies such as Wi-Fi RSS, Bluetooth Low Energy (BLE), magnetic field fingerprinting suffer from limitations in accuracy, scalability, and installation costs, reducing their suitability for seamless wayfinding.

Augmented Reality offers an optimistic substitute by providing real-time and interactive navigation experiences. Augmented reality enhances navigation by overlaying digital guidance onto the physical environment, allowing users to follow virtual prompts directly in their field of vision.

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This technology is already demonstrating value across sectors such as tourism, logistics, education, and field services, and its potential for mobile navigation applications is particularly significant. This study explores the fusion of Simultaneous Localization and Mapping (SLAM) with QR code-based repositioning. Although SLAM is effective for building real-time maps and tracking user location, it is susceptible to cumulative drift errors in dynamic environments. QR codes serve as precise reference anchors that recalibrate the SLAM system, consequently rectifying drift and enhancing durable stability. This fusion ensures high accuracy while maintaining cost-effectiveness, as QR codes are inexpensive, easy to deploy, and reliable under varying conditions.

This survey paper presents a cost-effective AR-based indoor navigation system that leverages built-in smartphone sensors, including accelerometers, gyroscopes, and cameras, alongside SLAM–QR fusion and the A* pathfinding algorithm. By integrating AR with these technologies, the system provides intuitive visual prompts that adapt to user movements, ensuring accurate guidance in a complex indoor environment. The proposed approach addresses the limitations of traditional methods by offering an interactive, scalable, and user-friendly solution, thus advancing location-based services and enabling reliable indoor navigation across diverse applications.

II. Related Work

[1] Multiple studies have explored indoor navigation systems using radio- based, vision-based, and hybrid technologies. Wong et al. developed a Wi-Fi–based localization system that utilizes signal strength measurements for indoor positioning [1]. Although widely used, Wi-Fi fingerprinting suffers from environmental noise and requires repeated calibration.

[2] Pradeep Kumar et al. presented an AR-based indoor navigation approach that provides interactive visual path guidance within large public buildings [4]. Their work highlights the potential of mobile AR in improving user experience but does not fully address localization accuracy.

[3] Munesh Kumar Sharma et al. introduced an AR navigation concept optimized for mobile devices, enabling real-time access to nearby structures and location-based information [5]. This approach demonstrates usability advantages but does not integrate SLAM correction mechanisms.

[4] Other studies have explored magnetic-field-based positioning, BLE beacons, and geomagnetic fingerprinting. However, these systems often face challenges related to installation costs, environmental interference, or drift.

[5] In 2015, R. Mur-Artal, J. M. M. Montiel, and J. D. Tardós introduced ORB-SLAM, a feature-based monocular SLAM system for real-time tracking and mapping [6]. The framework used ORB feature extraction, keyframe-based bundle adjustment, and loop closure detection to improve localization accuracy. Experiments on standard datasets showed that trajectory estimation accuracy improved by about 30 to 40% compared to PTAM, with low Absolute Trajectory Error (ATE) in indoor sequences. However, monocular scale ambiguity and long-term drift were still issues, which led to the need for integration with QR-based absolute correction.

[6] In 2021, C. Campos, R. Elvira, J. J. Gómez Rodríguez, J. M. M. Montiel, and J. D. Tardós proposed ORB-SLAM3 [7]. This system combined visual and inertial data and added multi-map capabilities. It reduced trajectory error by nearly 35% when compared to ORB-SLAM2 in the EuRoC indoor datasets. Adding IMU preintegration improved reliability during fast movements. However, despite its high accuracy, the system showed reduced performance in visually repetitive corridors. This highlights the need for marker-assisted relocalization.

TABLE I: TYPE SIZES FOR CAMERA-READY PAPERS

Positioning Technology	Features		
	Positioning accuracy range	Cost-effectiveness	Robustness
GPS	>40 m	Low	Weak indoor signals
Wi-fi	30-40 m [2]	Low	Multipath effect, time-consuming fingerprinting
BLE Beacon	10-20m [2]	High	Environmental interference
Magnetic field	2-6 m [2]	Low	Metal element interference
QR codes	1-3 m	High	Requires line of sight.
SLAM	0.5-2 m	High	High computational requirements.
Fusion (Wi-FI + Magnetic Field)	1-2 m	Low	Fingerprinting overhead.

[7] In 2018, T. Qin, P. Li, and S. Shen developed VINS-Mono, a visual-inertial odometry system based on nonlinear optimization [8]. The framework achieved localization accuracy with a drift of 1 to 2 percent over the traveled distance in indoor experiments. VINS-Mono improved robustness by about 20 to 30 percent compared

to purely visual methods under motion blur conditions. However, drift increased over longer trajectories, indicating that QR-based global pose anchoring could be beneficial.

[8] In 2011, E. Olson introduced the AprilTag fiducial system for reliable 6-DOF pose estimation [9]. Detection rates exceeded 95% accuracy in controlled indoor lighting. Pose estimation errors were usually below 2 cm at close range. While the system was very dependable near markers, its detection range and sensitivity to occlusion limited scalability without integration with continuous SLAM tracking.

[9] In 2021, Y. Lu, Z. Wang, and H. Li created an ARCore-based augmented reality indoor navigation system for campuses [10]. The system used visual-inertial tracking for path rendering and real-time guidance. User evaluations showed better navigation efficiency. However, tracking loss happened in visually repetitive areas. This emphasized the limitation of SLAM-based AR systems that do not include marker-based correction.

[10] In 2024, B. Bamdad, L. Zhu, and their team introduced the InCrowd-VI dataset for testing visual-inertial SLAM in busy indoor spaces [12]. The dataset featured moving obstacles and people blocking views to mimic real-world navigation situations. The results indicated a drop in performance in crowded scenes, highlighting the necessity for mixed localization methods like QR-assisted relocalization.

[11] In 2024, Lynam et al. presented a detailed survey on augmented reality navigation systems [13]. The study grouped approaches by localization strategies, including vision-based SLAM, marker-based positioning, and hybrid methods. The survey pointed out drift, scalability, and user interface limitations as major challenges in indoor AR navigation. This highlighted the importance of fusion-based localization systems.

[12] In 2022, Cadena et al. published a survey on visual SLAM techniques, examining feature-based, direct, and learning-based methods [14]. The review pointed out evaluation metrics like Absolute Trajectory Error (ATE) and Relative Pose Error (RPE). While SLAM techniques have improved significantly, the study stressed the ongoing problem of drift in large indoor areas. It suggested that integrating external references, such as QR markers, is important.

[12] In 2016, S. Lee and K. Lee suggested a QR code-based indoor positioning method that uses predefined marker coordinates [15]. The system reached a localization accuracy of about 96% in areas visible to the markers. While it was very accurate near QR anchors, navigation became less smooth between markers because there was no continuous pose estimation.

[13] In 2023, X. Liu, Y. Zhang, and J. Chen introduced a QR map-based indoor navigation system that includes IMU correction [16]. Experimental results showed an overall positioning accuracy of 94% to 97% in structured indoor environments. There was a drift reduction of nearly 25% compared to systems using only IMU. The system's performance relied heavily on marker density and lighting conditions.

[14] In 2020, M. Billinghurst and A. Clark looked into augmented reality interfaces for indoor navigation using Unity and AR frameworks. Their system displayed directional arrows and spatial cues based on maps created by SLAM [17]. User studies indicated improved spatial understanding. However, localization instability was still a problem in low-feature environments.

[15] In 2019, J. Engel, T. Schöps, and D. Cremers proposed Direct Sparse Odometry (DSO), a direct visual odometry method that minimizes photometric error [19]. Indoor tests showed better tracking stability, achieving 15 to 20% lower trajectory error compared to feature-based VO in low-texture scenes. However, long-term drift continued without loop closure or marker-based correction.

[16] In 2007, G. Klein and D. Murray introduced Parallel Tracking and Mapping (PTAM) for small augmented reality workspaces [20]. The system achieved real-time performance at over 30 FPS with reliable tracking in controlled environments. It demonstrated about 90% tracking stability in small indoor scenes. However, scalability and large-area consistency were limited without extra global reference mechanisms.

[17] In 2014, Christian Forster, Luca Carlone, Frank Dellaert, and Davide Scaramuzza introduced IMU preintegration techniques for visual-inertial navigation systems. Their optimization framework increased state estimation accuracy and lowered computational overhead [21]. Even with better robustness, long-term drift persisted, showing the potential benefits of integrating fiducial anchors.

[18] In 2022, H. Wang and colleagues developed a hybrid SLAM, AprilTag indoor navigation system [22]. This system combined continuous SLAM tracking with periodic marker-based correction. As a result, it reduced trajectory error by about 28 to 32% compared to standalone SLAM. Experimental tests in indoor robot navigation showed better global consistency. However, marker occlusion lowered efficiency in messy environments.

[19] In 2018, A. Kim and R.M. Eustice studied strong visual SLAM in changing indoor settings [23]. Their system included loop closure and strong outlier rejection methods. While localization got better in moderately dynamic scenes, significant crowd interference still led to failures. This pushed the need for adding static QR anchors.

[20] In 2021, Sucar et al. proposed iMAP, a real-time dense neural SLAM approach for indoor scenes [24]. The method used implicit neural representations to create detailed 3D maps. While it improved mapping quality, the high computational demands made it difficult to use in mobile AR navigation.
[21] In 2019, Zhang and Scaramuzza conducted a survey on visual-inertial odometry methods for mobile platforms [25]. The study examined tightly coupled and loosely coupled fusion strategies. The authors found that combining VIO with absolute landmark references greatly improves global consistency in indoor environments.
[22] In 2020, A. Nüchter and colleagues studied multi-session indoor mapping with loop closure and global optimization [26]. This method allowed for consistent map alignment across sessions. However, initialization and re-localization errors continued to occur without fixed anchor references.
[23] In 2023, J. Park and S. Kim proposed an AR-based indoor navigation system that integrates QR anchors with SLAM tracking [27]. This hybrid approach achieved an overall localization accuracy of 97%. It reduced drift by nearly 30% compared to pure SLAM-based AR navigation. The system showed smoother AR path rendering and improved relocalization reliability. However, the best marker placement strategy is still an open research question.

III. System Components and Workflow

Indoor navigation research increasingly relies on camera-based and sensor-assisted localization techniques to address the limitations of traditional radio-frequency methods. Recent literature highlights the importance of combining Simultaneous Localization and Mapping (SLAM), marker-based anchor detection, and augmented reality (AR) overlays to achieve reliable guidance in complex indoor environments. SLAM serves as the foundation for vision-based indoor positioning by using RGB camera frames and inertial sensor data to estimate device pose while incrementally constructing a 3D representation of the environment. Algorithms such as ORB-SLAM2 and related visual feature extraction methods have demonstrated strong performance in indoor navigation scenarios, offering robust keypoint detection and visual-inertial odometry capabilities. AR platforms such as ARCore and ARKit extend these pipelines through enhanced plane detection and real-time point-cloud reconstruction, although drift accumulation remains a known limitation when feature availability decreases or when navigating through highly repetitive indoor structures.

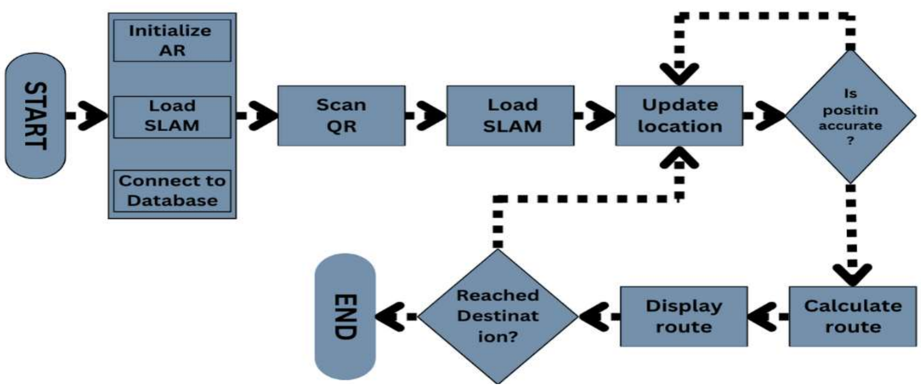

Figure 1. System Workflow

To support path computation, many systems translate the SLAM map into a navigable representation such as a spatial mesh or NavMesh, which distinguishes walkable surfaces from obstacles and static boundaries. Once such a representation is available, heuristic search algorithms—particularly the A* search—are commonly employed to identify an optimal route between the user's estimated position and a selected destination[19]. These methods offer predictable performance and are well suited for constrained indoor layouts where dynamic rerouting may be required.
A complementary technique widely discussed in recent studies is the use of QR codes or fiducial markers as absolute reference points for correcting SLAM drift. QR-based repositioning enables instantaneous pose correction by aligning the SLAM-derived estimate with a known coordinate encoded within the marker. This hybrid approach leverages the strengths of both continuous visual tracking and discrete marker-based calibration, producing more stable localization in environments where standalone SLAM becomes unreliable due to lighting variations or insufficient visual features.

AR visualization modules further enhance navigation by overlaying directional cues, labels, and markers directly onto the user's camera view, enabling intuitive understanding of spatial instructions. These overlays rely on updated world coordinates produced through SLAM and marker-based corrections, ensuring that rendered guidance adapts dynamically as the user moves. Backend components such as Firebase or SQLite are often incorporated to store floor layouts, marker coordinates, and semantic information, supporting scalable deployment across large environments.

When integrated, these components form a characteristic workflow seen across hybrid indoor navigation architectures: continuous pose estimation through SLAM, drift mitigation through QR-based re-anchoring, route computation using heuristic search, and AR-based visualization for user interaction. This combination demonstrates a strong technological synergy between sensing, mapping, drift correction, spatial reasoning, and real-time rendering, contributing significantly to the reliability and usability of indoor navigation systems.

IV. Comparative Analysis

Indoor navigation technologies have changed from signal-based systems to intelligent vision-driven spatial computing frameworks. Traditional indoor navigation primarily depends on Wi-Fi fingerprinting, Bluetooth Low Energy (BLE) beacons, RFID tags, or standalone QR code positioning. While these methods help with location awareness, they do not provide continuous spatial understanding or immersive interaction. In contrast, modern systems that integrate Simultaneous Localization and Mapping (SLAM), QR-based relocalization, and Augmented Reality (AR) create a hybrid framework that improves both localization accuracy and user experience.

Classic Wi-Fi or BLE-based systems estimate position using signal strength measurements. Although popular because they are easy to set up, their localization accuracy usually ranges from 2 to 5 meters and is very sensitive to environmental interference. Signal fluctuations caused by multipath effects, structural changes, and moving obstacles lower reliability. Additionally, these systems only offer coordinate-level positioning, which requires separate 2D map interfaces for navigation. This indirect visualization increases the cognitive load on users and often leads to navigation errors[25].

Standalone QR-based indoor navigation systems boost absolute localization accuracy, often achieving sub-meter precision near visible markers. By placing QR codes at set waypoints, the camera estimates its position relative to the detected marker. However, this method provides discrete localization updates instead of continuous tracking. Between marker detections, the system loses motion continuity, leading to segmented navigation and a less smooth experience[15]. A high density of markers is also necessary for large buildings, raising infrastructure and maintenance costs.

Pure SLAM-based indoor navigation systems, particularly visual or visual-inertial SLAM approaches, get rid of infrastructure dependency by allowing continuous real-time pose estimation and environment mapping. These systems create spatially consistent maps while tracking camera movement, making them suitable for AR-based applications. However, SLAM systems can suffer from cumulative drift over long paths. In environments with repetitive textures, low-feature areas, or busy crowds, tracking instability and relocalization failures can happen. Although loop closure techniques help reduce drift, they are not always enough in large indoor spaces.

Combining QR markers with SLAM addresses these issues by merging continuous tracking with periodic absolute correction. In hybrid systems, SLAM offers real-time motion estimation and mapping, while QR markers act as global anchors for recalibration. When a QR marker is detected, accumulated drift is corrected, enhancing global consistency. Studies indicate that hybrid SLAM-marker systems can decrease trajectory error by about 25 to 35% compared to standalone SLAM methods[28]. This balance allows for scalable deployment with fewer markers placed strategically at key decision points, like intersections or staircases.

Integrating Augmented Reality further improves usability. Instead of looking at 2D maps, users get intuitive navigation cues directly overlaid on the real-world environment, such as directional arrows and spatial indicators. AR lowers cognitive load, boosts navigation efficiency, and reduces wrong turns. When supported by stable QR–SLAM fusion, AR overlays stay accurately aligned with the physical environment.

Overall, traditional systems provide basic localization but limited spatial intelligence. Pure SLAM offers autonomy but struggles with drift. The fusion of QR, SLAM, and AR combines accuracy, continuity, and intuitive guidance, making it a strong solution for complex indoor environments like universities, hospitals, and commercial buildings.

TABLE II. COMPARATIVE ANALYSIS BETWEEN PRESENT INDOOR NAVIGATION SYSTEMS AND INDOOR NAVIGATION SYSTEM USING FUSION OF QR POSITIONING AND SLAM.

Parameter	Conventional Indoor Navigation (Wi-Fi / BLE / QR Only)	Pure SLAM-Based Indoor Navigation	Fusion of QR + SLAM + AR (Proposed Approach)
Parameter	Conventional Indoor Navigation (Wi-Fi / BLE / QR Only)	Pure SLAM-Based Indoor Navigation	Fusion of QR + SLAM + AR (Proposed Approach)
Localization Accuracy	2–5 m (Wi-Fi/BLE); <1 m near QR markers	High short-term accuracy; drift accumulates over time	High continuous accuracy; drift reduced by ~25–35% using QR correction
Tracking Continuity	Discrete updates (QR) or signal-based estimation	Continuous real-time pose tracking	Continuous SLAM tracking + periodic global correction
Drift Handling	No drift modeling (signal-based); none between QR scans	Cumulative drift over long trajectories	Drift corrected when QR anchor detected
Infrastructure Requirement	High (dense beacons or QR placement)	Minimal infrastructure	Moderate; sparse QR anchors at key points
Scalability (Large Buildings)	Limited; requires dense deployment	Good but drift increases with scale	High scalability with strategic marker placement
Performance in Dynamic Environments	Signal instability under crowd movement	May fail in low-feature or dynamic scenes	More robust; SLAM maintains tracking while QR ensures recalibration
User Interface	2D map-based navigation	2D or AR overlay	Immersive AR guidance with spatial alignment
Cognitive Load	Higher (interpret map manually)	Moderate	Lower due to real-world AR overlays
Cost Efficiency	Moderate to High (beacon maintenance)	Low infrastructure cost	Balanced; limited marker deployment

V. FUTURE WORK

Future research in indoor navigation is expected to focus on improving accuracy, robustness, and scalability across diverse environments. One direction involves incorporating AI-enhanced perception and semantic understanding to strengthen SLAM performance in feature-poor or dynamic areas. Vertical navigation also requires further attention, where techniques such as barometric sensing, multi-level SLAM, or elevator-aware localization can support seamless floor transitions. Hardware advancements—including depth sensors, LiDAR, and ultra-wideband radios—may complement existing vision-based approaches by providing more reliable positional cues

Cloud-supported mapping represents another promising avenue, allowing large indoor spaces to maintain continuously updated layouts through collaborative user contributions[22]. This could enable multi-user AR navigation with shared anchors and synchronized spatial information. Additionally, future systems may emphasize adaptive AR interfaces that adjust guidance based on user context, accessibility needs, or real-time crowd conditions. Collectively, these directions indicate that next-generation indoor navigation solutions will rely on a tighter integration of sensing, machine intelligence, and context-aware AR visualization..

VI. CONCLUSIONS

This survey shows that indoor navigation continues to face challenges in accuracy, stability, and scalability, especially in environments where traditional radio-based methods perform poorly. Recent literature demonstrates a growing reliance on SLAM, QR-based repositioning, and AR visualization, as these techniques complement one another in mitigating drift and improving user guidance. Although vision-based and hybrid methods offer notable advantages, they remain sensitive to environmental conditions, device limitations, and multi-floor transitions. Overall, current research indicates that future progress will depend on more robust fusion of visual sensing, marker-based correction, and intelligent AR interfaces to develop reliable and adaptable indoor navigation systems suitable for diverse real-world settings.

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